

5.3 ACT-UP: A Toolkit for Hampton, Cognitive Modeling Composition, Reuse and Integration



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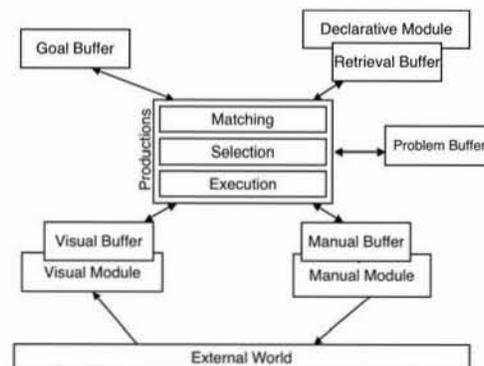
ACT-UP: A Cognitive Modeling Toolkit for Composition, Reuse and Integration

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ACT-R Cognitive Architectures

- Computational implementation of unified theory of cognition
- Commitment to task-invariant mechanisms
- Modular organization
- Limited capacity
- Hybrid symbolic statistical processes



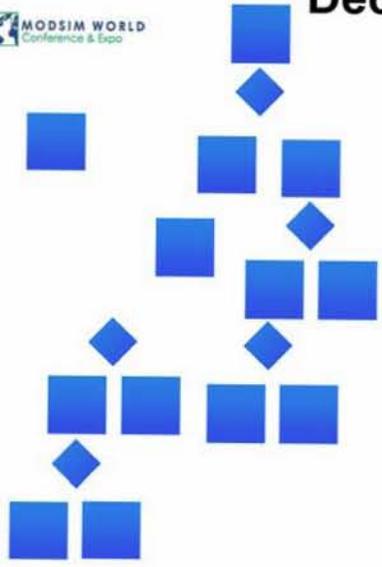
Motivations and Applications

- **Philosophy:** Unified understanding of the mind.
- **Psychology:** Account for experimental data.
- **Education:** Provide cognitive models for intelligent tutoring systems and other learning environments.
- **Human Computer Interaction:** Evaluate artifacts and help in their design.
- **Computer Generated Forces:** Provide cognitive agents to inhabit training environments & games.
- **Neuroscience:** Provide a framework for interpreting data from brain imaging.

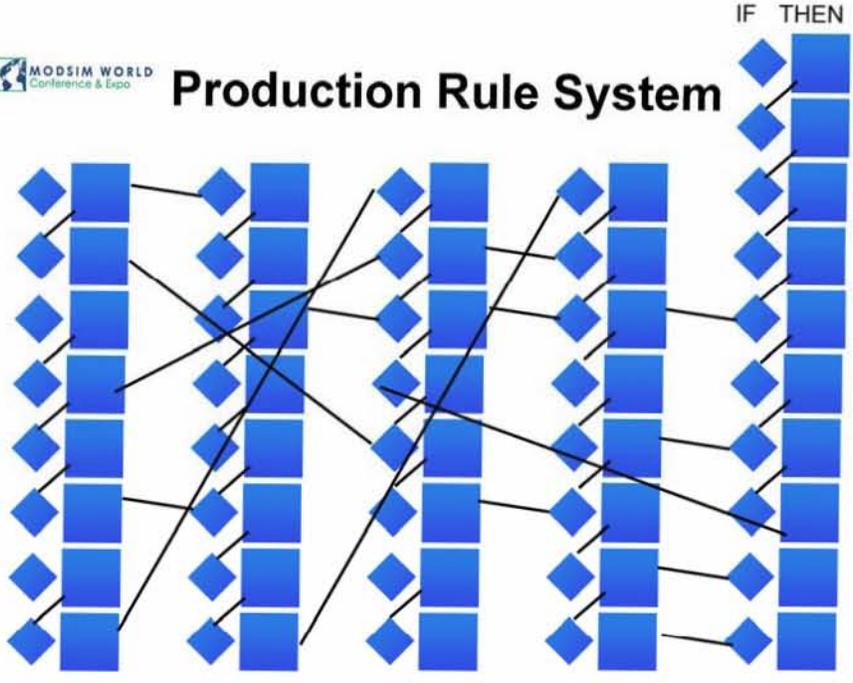
Goals

- Enable the implementation of more complex ACT-R models
- Scale up cognitive models to simulate learning / adaptation in communities (e.g., about 1,000 models in parallel)
- Treat models as hard claims
 - Evaluate each specified component against data
 - Underspecify the rest and fit free parameters

Decomposition



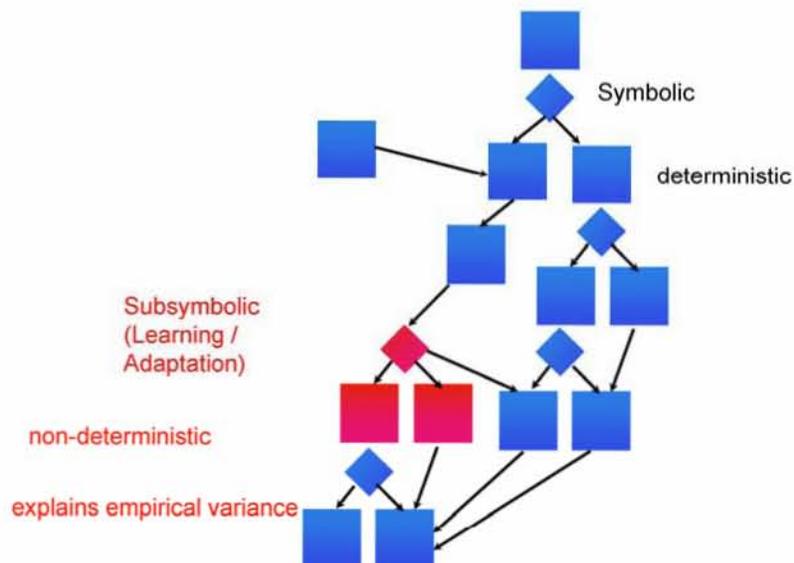
Production Rule System



The Argument

- **Constraints:** Architectural advances require further constraints
- **Scaling it up:** Complex tasks, broad coverage of behavior (e.g., linguistic), use of microstrategies and predictive modeling may serve to motivate further architectural constraints
- **Difficulties:** ACT-R is heavily constrained already, and models are difficult to develop, reuse and exchange
- **We need to produce models at a higher abstraction level**
 - However, we'd like to leverage successful cognitive modules, describing memory retention, cue-based retrieval, routinization, reinforcement learning

Cognitive Strategy



Priming Model



Crucial request of a chunk from declarative memory



- Only a small portion of the model explains the behavioral data at hand
- The rest explains that the task can be accomplished in principle with a parallel architecture and with specific cognitive representations (chunk types)



Production Systems vs. assembly language

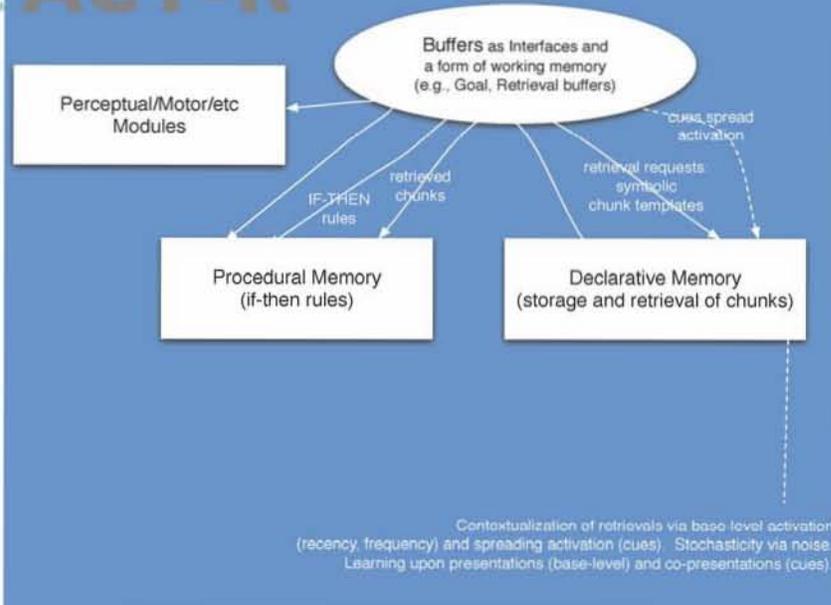
```
evensum:  cir.1  D1      ;Zero-out
           add.1  D0,D1   ;Accumulator
sumloop:  add.1  D0,D1   ;Add current
           ;counter value to
accumulator
           subq  #1,D0   ;Decrement
           ;counter by one
           bne  sumloop ;until it
           ;reaches zero
           muls #2,D1   ;Double sum to account
           ;for even numbers
           rts                ;Return
           ;to caller
```



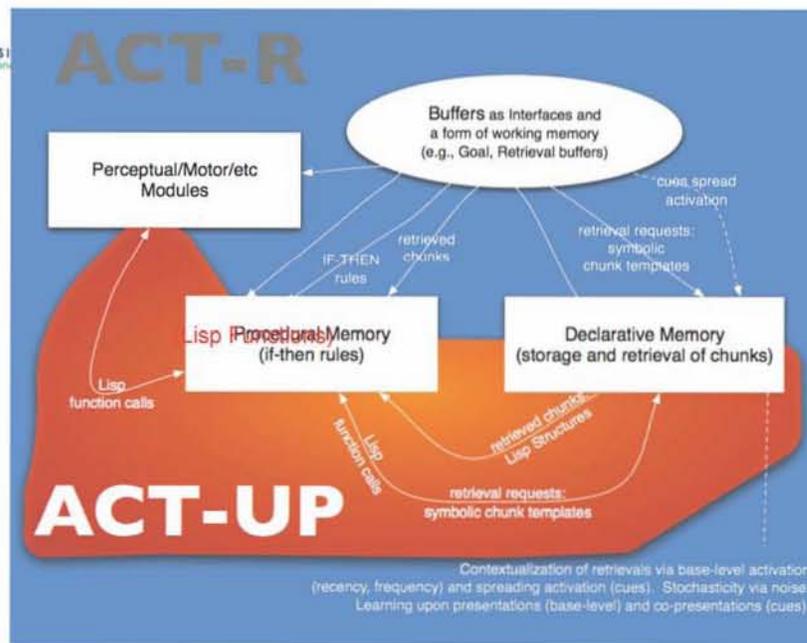
~1990



ACT-R



ACT-R



ACT-UP

- A stand-alone system on the basis of Common Lisp
- targets an audience that can write simple Lisp programs (unlike, e.g., CogTool)
- Toolbox approach to ACT-R
 - light-weight: it's a Lisp library
 - does not produce production rules (ACT-R/Lisa, ACT-Simple, CogTool)
- Not aimed at implementing all constraints of ACT-R 6 (unlike Java ACT-R, Python ACT-R)

Declarative Memory

- ``define-chunk-type'`
 - types are optional
- ``make-count-order'`
- ``learn-chunk'`
- ``defrule'`
- ``retrieve-chunk'`
- ``count-order-second'`

```

;; ACT-R parameters
(setq *lf* .05)
(setq *rt* -1)

;;; Defining chunk type
(define-chunk-type count-order first second)

```

ACT-UP Code

ACT-UP is not ACT-R 6...

- ACT-UP Interface is synchronous
 - Serial execution
 - Deterministic strategies defined as programs
- Parallelism (e.g., perceptual/motor modules) possible [not implemented]
- Non-deterministic rule choice is possible
 - Reinforcement-learning as in ACT-R 6

PM / Utility learning

- `choose-coin`
- calls either `decide-heads` or `decide-tails`
- `assign-reward` reinforces the decision
- Exact production rules are underspecified,
 - but decision-making point is explicit
- Choice model replicates ACT-R and empirical results

```

;; Experimental environment
(defun toss-coin ()
  (if (< (random 1.0) .9) 'heads 'tails))

;; The Model
;;; Rules that return the choice as symbol heads or tails

(defrule decide-tails ()
  :group choose-coin
  'tails)

(defrule decide-heads ()
  :group choose-coin
  'heads)

```

Debugging

```
(defrule count-model (arg1 arg2)
  "Count from ARG1 to ARG1.
  ARG1 is the starting point and ARG2 is the ending point.
  Each increment is 1 unit."
  (speak arg1)
  (if (not (eq arg1 arg2))
      (let ((p (debug-detail (retrieve-chunk (list :chunk-type 'count-order
                                                  :first arg1))))))
        (if p
            (count-model (count-order-second p) arg2))
          ;; else return end point
          arg2))
```

Debugging

CL-USER> (debug-detail (do-it 1))

```
make-match-chunk (make-TYPE*): No such chunk in DM. Returning new chunk (not in DM) of name LOSE
Presentation of chunk LOSE (MP: NIL t=72761.26. M: MODEL521436, t=0.
Implicitly creating chunk of name LOST.
Presentation of chunk LOST (MP: NIL t=72761.26. M: MODEL521436, t=0.
Implicitly creating chunk of name BLANK.
Presentation of chunk BLANK (MP: NIL t=72761.305. M: MODEL521436, t=72761.305.
make-match-chunk (make-TYPE*): No such chunk in DM. Returning new chunk (not in DM) of name HAVE
Presentation of chunk HAVE (MP: NIL t=72761.445. M: MODEL521436, t=72761.445.
Implicitly creating chunk of name HAD.
Presentation of chunk HAD (MP: NIL t=72761.445. M: MODEL521436, t=72761.445.
Group PAST-TENSE-MODEL with 1=0 matching rules, choosing rule PTMODEL (Utility 5.0709996)
Group FORM-PAST-TENSE with 3=0 matching rules, choosing rule STRATEGY-WITHOUT-ANALOGY (Utility 5.2259957)
retrieve-chunk:
  spec: (CHUNK-TYPE PASTTENSE VERB GET)
  cues: NIL
  pmot: NIL
Filtered 0 matching chunks.
retrieved none out of 0 matching chunks.
NIL
Assigning reward 3.9
Assigning reward 3.853125 to STRATEGY-WITHOUT-ANALOGY. STRATEGY-WITH-ANALOGY remains best regular rule in group FORM-PAST-TENSE.
Assigning reward 0.0 to PTMODEL. Best regular rule among alternatives in group PAST-TENSE-MODEL!
NIL
CL-USER> |
```

Implemented Models

- 10 Classic models implemented:
 - count, addition, siegler, zbrodoff, paired, fan, sticks, semantic, choice, past-tense

* past-tense not yet complete

Efficiency

- Sentence production (syntactic priming) model
 - 30 productions in ACT-R, 720 lines of code
 - 82 lines of code in ACT-UP (3 work-days)
 - ACT-R 6: 14 sentences/second
 - ACT-UP: 380 sentences/second

Scalability

- Language evolution model
 - Simulates domain vocabulary emergence (ICCM 2009, JCSR 1010)
 - 40 production rules in ACT-R (could not prototype)
 - 8 participants interacting in communities
- In larger community networks: 1000 agents, 84M interactions (about 1 minute sim. time each), 37 CPU hours

Rapid prototyping/Reuse

- Dynamic Stocks&Flows model (JAGI 2010)
 - Competition entry, model written in < 1 person-month
 - Instance-based learning (IBL, Gonzales&Lebiere 2003)
 - Blending (Wallach&Lebiere 2003)
 - free parameters (timing) estimated from example data
 - Model generalized to novel conditions
 - (... NOT. but it did so better than others.)
- Same IBL/blending micro-strategy was re-used directly in a *Lemonade Stand Game* entry to a 2009 competition (BRIMS 2010)

Drawbacks

- Less established code-base than ACT-R 6
- Lisp
- Lack of architectural timing predictions from rule matching
- Lack of parallelism (planned: fall 2010)
- lack of perception/motor modules
 - Will be available in ACT/Simple-style interface (Salvucci&Lee 2003)

Beta-Test

- **Limited Release** of ACT-UP test version
 - comes with 10 example models
 - 4 tutorials (paralleling the ACT-R 6 ones)
 - Full API documentation plus *How-do-I...* document
- Testing period: Fall 2010
- Task: implement 1-2 models of your own
- Review letter requested (journal-review style)